What Is Econometrics?

From Economic Questions to Empirical Answers

Jake Anderson

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Outline

1. Why Econometrics?
2. From Economic Models to Econometric Models
3. Correlation Is Not Causation
4. Data Types
5. The Econometrics Pipeline
6. What Lies Ahead

A Simple Economic Question

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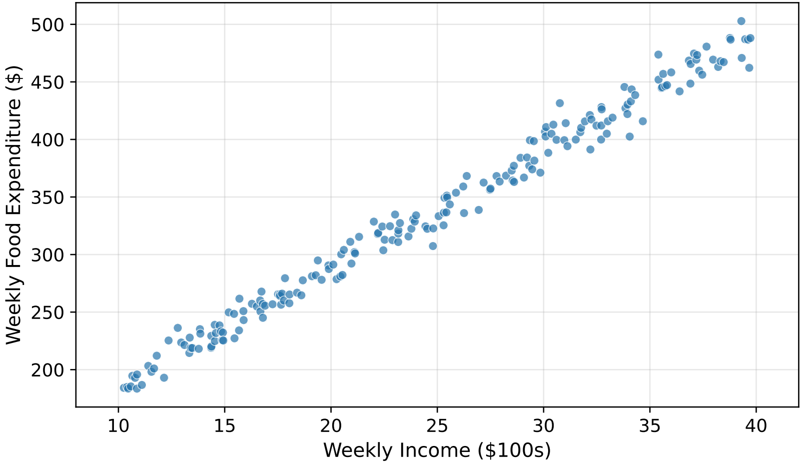
That method is **econometrics**.

Let’s Look at Some Data

Here is food expenditure data from 200 households with weekly income between $1,000 and $4,000:



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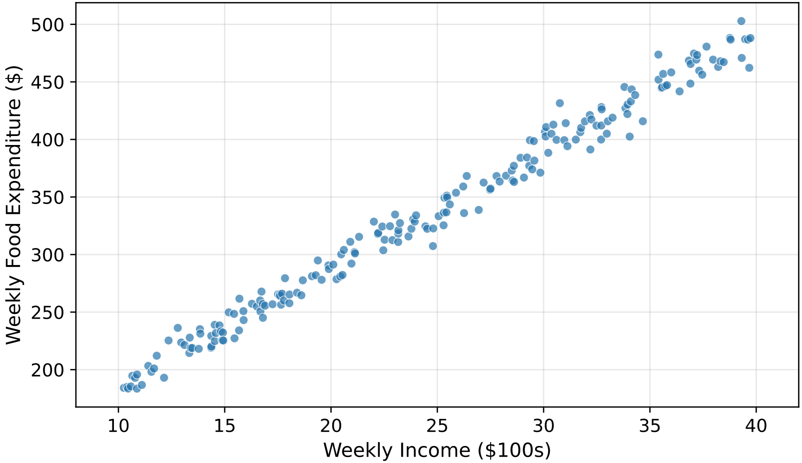

What Is Econometrics?

Econometrics uses economic theory, data, and statistical tools to:

1. **Estimate** economic relationships (how much does x affect y?)
2. **Predict** economic outcomes (what will GDP be next quarter?)
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$\Longrightarrow$ Econometrics adds an **economic model** to guide which statistics to compute and how to interpret them.

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The values that answer these questions (elasticities, multipliers, marginal effects) are unknown **parameters**. Econometrics estimates them from data.

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The economic model is a starting point. To get numbers from data, we need to be more specific.

A First Attempt: Averages by Income Group

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This confirms the pattern: food spending rises with income

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$\Longrightarrow$ We need a **model** that summarizes the relationship with a formula we can evaluate at *any* income level.

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$\Longrightarrow$ The error explains why two households with the same income spend different amounts on food.

Estimation: Fitting the Line to Data

Using data from 200 households, econometric methods give us **estimates** $\hat{\beta}_1$ and $\hat{\beta}_2$. A hat ($\hat{\ }$) denotes a value computed from data, as opposed to the true unknown parameter.

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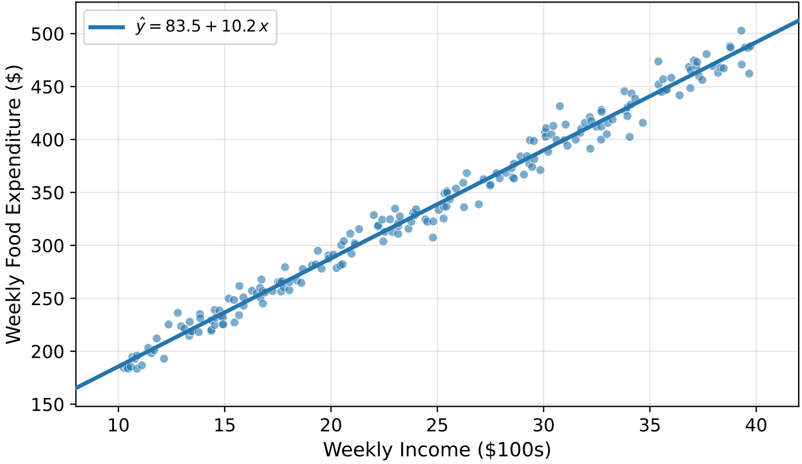

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Question: Does skipping *cause* lower grades?

Why $\hat{\beta}_2$ May Not Be Causal

Students who skip may also:

- Work long hours at a job
- Be less motivated to study
- Have personal circumstances affecting both attendance and grades
- Already know the material well enough that they don't need help
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$\implies$ $\hat{\beta}_2$ captures the *association* between skipping and grades, not necessarily the causal effect of skipping alone.

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Not every “how much” question requires a causal answer:

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- Adding control variables (multiple regression)
- Hypothesis testing and model specification
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$\implies$ Distinguishing correlation from causation is a central challenge of econometrics.

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Some experiments are also **unethical**: you cannot randomly assign people to get cancer, or randomly sentence people to incarceration, just to measure the effect.

Cross-Section Data

Observations on **many units at one point in time**.

Individual	Race	Education	Sex	Wage ($/hr)
1	Black	12	Female	15.50
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$\Longrightarrow$ We see variation *across* individuals, but we have no "before and after."

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The **same variable** recorded at regular intervals over time.

Year	Real GDP (Billions, 2009 $)
2010	14,784
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$\Longrightarrow$ We see how things change *over time*, but observations are typically not independent (today's GDP depends on yesterday's).

Panel (Longitudinal) Data

The **same units** observed over **multiple time periods**.

Farm	Year	Output	Area	Labor
1	1995	510	13	28
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This course walks through each step. By the end, you will be able to run this pipeline yourself.

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We will return to this example throughout the course as we develop each step.

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- **Chapters 2–3:** The simple linear regression model and its properties
- **Chapters 4–6:** Inference, prediction, and the multiple regression model
- **Chapters 7–9:** Indicator variables, heteroskedasticity, regression specification
- **Later chapters:** Time series, simultaneous equations, panel data

We estimated $\hat{\beta}_2 \approx 10.4$ today. But how confident should we be in that number? Could it be 5, or 15, and we just got unlucky with our sample? That is where we start next time.

Thank you!

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